2 Announcements

We will be releasing HW1 today
- It is due in 2 weeks (4/18 at 23:59pm)
- The homework is long
  - Requires proving theorems as well as coding
- Please start early

Recitation sessions:
- Spark Tutorial and Clinic:
  Today 2:30-4:20pm in GWN 201 (Gowen Hall)
Frequent Itemset Mining & Association Rules
Association Rule Discovery

Supermarket shelf management – Market-basket model:

- **Goal:** Identify items that are bought together by sufficiently many customers
- **Approach:** Process the sales data collected with barcode scanners to find dependencies among items
- **A classic rule:**
  - If someone buys diaper and milk, then he/she is likely to buy beer
  - Don’t be surprised if you find six-packs next to diapers!
The Market-Basket Model

- **A large set of items**
  - e.g., things sold in a supermarket

- **A large set of baskets**
  - Each basket is a small subset of items
    - e.g., the things one customer buys on one day

- **Discover association rules:**
  People who bought \{x,y,z\} tend to buy \{v,w\}
  - Example application: Amazon

**Input:**

<table>
<thead>
<tr>
<th>Basket</th>
<th>Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Bread, Coke, Milk</td>
</tr>
<tr>
<td>2</td>
<td>Beer, Bread</td>
</tr>
<tr>
<td>3</td>
<td>Beer, Coke, Diaper, Milk</td>
</tr>
<tr>
<td>4</td>
<td>Beer, Bread, Diaper, Milk</td>
</tr>
<tr>
<td>5</td>
<td>Coke, Diaper, Milk</td>
</tr>
</tbody>
</table>

**Output:**

**Rules Discovered:**

- \{Milk\} --> \{Coke\}
- \{Diaper, Milk\} --> \{Beer\}
More generally

- A general many-to-many mapping (association) between two kinds of things
  - But we ask about connections among “items”, not “baskets”
- Items and baskets are abstract:
  - For example:
    - Items/baskets can be products/shopping basket
    - Items/baskets can be words/documents
    - Items/baskets can be basepairs/genes
    - Items/baskets can be drugs/patients
Applications – (1)

- **Items** = products; **Baskets** = sets of products someone bought in one trip to the store
- **Real market baskets:** Chain stores keep TBs of data about what customers buy together
  - Tells how typical customers navigate stores, lets them position tempting items:
    - Apocryphal story of “diapers and beer” discovery
    - Used to position potato chips between diapers and beer to enhance sales of potato chips
- **Amazon’s ‘people who bought X also bought Y’**
Applications – (2)

- **Baskets** = sentences; **Items** = documents in which those sentences appear
  - Items that appear together too often could represent plagiarism
  - Notice items do not have to be “in” baskets

- **Baskets** = patients; **Items** = drugs & side-effects
  - Has been used to detect combinations of drugs that result in particular side-effects
  - **But requires extension:** Absence of an item needs to be observed as well as presence
Outline

First: Define
- Frequent itemsets
- Association rules:
  - Confidence, Support, Interestingness

Then: Algorithms for finding frequent itemsets
- Finding frequent pairs
- A-Priori algorithm
- PCY algorithm
Frequent Itemsets

- **Simplest question**: Find sets of items that appear together “frequently” in baskets
- **Support** for itemset $I$: Number of baskets containing all items in $I$
  - (Often expressed as a fraction of the total number of baskets)
- Given a **support threshold** $s$, then sets of items that appear in at least $s$ baskets are called *frequent itemsets*

<table>
<thead>
<tr>
<th>TID</th>
<th>Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Bread, Coke, Milk</td>
</tr>
<tr>
<td>2</td>
<td>Beer, Bread</td>
</tr>
<tr>
<td>3</td>
<td>Beer, Coke, Diaper, Milk</td>
</tr>
<tr>
<td>4</td>
<td>Beer, Bread, Diaper, Milk</td>
</tr>
<tr>
<td>5</td>
<td>Coke, Diaper, Milk</td>
</tr>
</tbody>
</table>

Support of \{Beer, Bread\} = 2
Example: Frequent Itemsets

- **Items** = \{milk, coke, pepsi, beer, juice\}
- **Support threshold** = 3 baskets
  
  \begin{align*}
  B_1 &= \{m, c, b\} & B_2 &= \{m, p, j\} \\
  B_3 &= \{m, b\} & B_4 &= \{c, j\} \\
  B_5 &= \{m, p, b\} & B_6 &= \{m, c, b, j\} \\
  B_7 &= \{c, b, j\} & B_8 &= \{b, c\}
  \end{align*}

- **Frequent itemsets**: \{m\}, \{c\}, \{b\}, \{j\}, \{m, b\}, \{b, c\}, \{c, j\}. 
Define: Association Rules

- **Define: Association Rules:** If-then rules about the contents of baskets
- \( \{i_1, i_2, \ldots, i_k\} \rightarrow j \) means: “if a basket contains all of \( i_1, \ldots, i_k \) then it is **likely** to contain \( j \)”
- In practice there are many rules, want to find significant/interesting ones!
- **Confidence** of association rule is the probability of \( j \) given \( I = \{i_1, \ldots, i_k\} \)

\[
\text{conf}(I \rightarrow j) = \frac{\text{support}(I \cup j)}{\text{support}(I)}
\]
Interesting Association Rules

- Not all high-confidence rules are interesting
  - The rule \( X \rightarrow \text{milk} \) may have high confidence for many itemsets \( X \), because milk is just purchased very often (independent of \( X \)) and the confidence will be high.
  - **Interest** of an association rule \( I \rightarrow j \):
    - abs. difference between its confidence and the fraction of baskets that contain \( j \)
    
    \[
    \text{Interest}(I \rightarrow j) = |\text{conf}(I \rightarrow j) - \Pr[j]| \]

- Interesting rules are those with high positive or negative interest values (usually above 0.5)
Example: Confidence and Interest

\[ B_1 = \{m, c, b\} \quad B_2 = \{m, p, j\} \]
\[ B_3 = \{m, b\} \quad B_4 = \{c, j\} \]
\[ B_5 = \{m, p, b\} \quad B_6 = \{m, c, b, j\} \]
\[ B_7 = \{c, b, j\} \quad B_8 = \{b, c\} \]

- **Association rule:** \( \{m, b\} \rightarrow c \)
  - **Support** = 2
  - **Confidence** = \( \frac{2}{4} = 0.5 \)
  - **Interest** = \( |0.5 - \frac{5}{8}| = \frac{1}{8} \)
    - Item \( c \) appears in \( \frac{5}{8} \) of the baskets
    - The rule is not very interesting!
Problem: Find all association rules with support $\geq s$ and confidence $\geq c$

Note: Support of an association rule is the support of the set of items in the rule (left and right side)

Hard part: Finding the frequent itemsets!

If $\{i_1, i_2, \ldots, i_k\} \rightarrow j$ has high support and confidence, then both $\{i_1, i_2, \ldots, i_k\}$ and $\{i_1, i_2, \ldots, i_k, j\}$ will be “frequent”

$$\text{conf}(I \rightarrow j) = \frac{\text{support}(I \cup j)}{\text{support}(I)}$$
Mining Association Rules

- **Step 1:** Find all frequent itemsets \( I \)
  - (we will explain this next)
- **Step 2:** Rule generation
  - For every subset \( A \) of \( I \), generate a rule \( A \rightarrow I \setminus A \)
    - Since \( I \) is frequent, \( A \) is also frequent
    - **Variant 1:** Single pass to compute the rule confidence
      - \( \text{confidence}(A,B \rightarrow C,D) = \text{support}(A,B,C,D) / \text{support}(A,B) \)
    - **Variant 2:**
      - **Observation:** If \( A,B,C \rightarrow D \) is below confidence, so is \( A,B \rightarrow C,D \)
      - Can generate “bigger” rules from smaller ones!
  - **Output the rules above the confidence threshold**
Example

- $B_1 = \{m, c, b\}$
- $B_2 = \{m, p, j\}$
- $B_3 = \{m, c, b, n\}$
- $B_4 = \{c, j\}$
- $B_5 = \{m, p, b\}$
- $B_6 = \{m, c, b, j\}$
- $B_7 = \{c, b, j\}$
- $B_8 = \{b, c\}$

- **Support threshold** $s = 3$, **confidence** $c = 0.75$

- **Step 1)** Find frequent itemsets:
  - $\{b,m\} \quad \{b,c\} \quad \{c,m\} \quad \{c,j\} \quad \{m,c,b\}$

- **Step 2)** Generate rules:
  - $b \rightarrow m: c = \frac{4}{6}$
  - $b \rightarrow c: c = \frac{5}{6}$
  - $b,c \rightarrow m: c = \frac{3}{5}$
  - $m \rightarrow b: c = \frac{4}{5}$
  - $\ldots$
  - $b,m \rightarrow c: c = \frac{3}{4}$
  - $b \rightarrow c,m: c = \frac{3}{6}$
Compacting the Output

- To reduce the number of rules, we can post-process them and only output:
  - **Maximal frequent itemsets:**
    No immediate superset is frequent
    - Gives more pruning
  - **Closed itemsets:**
    No immediate superset has the same support (> 0)
    - Stores not only frequent information, but exact supports/counts
### Example: Maximal/Closed

<table>
<thead>
<tr>
<th></th>
<th>Support</th>
<th>Maximal(s=3)</th>
<th>Closed</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>4</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>B</td>
<td>5</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>C</td>
<td>3</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>AB</td>
<td>4</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>AC</td>
<td>2</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>BC</td>
<td>3</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>ABC</td>
<td>2</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

- **Support**: The number of transactions containing each itemset.
- **Maximal(s=3)**: Indicates if the itemset is maximal with respect to the support threshold of 3.
- **Closed**: Indicates if the itemset is closed.

**Frequent, but superset BC also frequent.**

**Frequent, and its only superset, ABC, not freq.**

**Superset BC has same support.**

**Its only superset, ABC, has smaller support.**
Step 2: Finding Frequent Itemsets
Itemsets: Computation Model

- **Back to finding frequent itemsets**
- Typically, data is kept in flat files rather than in a database system:
  - Stored on disk
  - Stored basket-by-basket
  - Baskets are **small** but we have many baskets and many items
    - Expand baskets into pairs, triples, etc. as you read baskets
    - Use $k$ nested loops to generate all sets of size $k$

**Note:** We want to find frequent itemsets. To find them, we have to count them. To count them, we have to enumerate them.
Computation Model

- The true cost of mining disk-resident data is usually the **number of disk I/Os**

- In practice, association-rule algorithms read the data in **passes** – all baskets read in turn

- We measure the cost by the **number of passes** an algorithm makes over the data

<table>
<thead>
<tr>
<th>Item</th>
<th>Item</th>
<th>Item</th>
<th>Item</th>
<th>Item</th>
<th>Item</th>
<th>Item</th>
<th>Item</th>
<th>Item</th>
<th>Item</th>
<th>Item</th>
<th>Etc.</th>
</tr>
</thead>
</table>

Items are positive integers, and boundaries between baskets are $-1$. 
Main-Memory Bottleneck

- For many frequent-itemset algorithms, **main-memory** is the critical resource
  - As we read baskets, we need to count something, e.g., occurrences of pairs of items
  - The number of different things we can count is limited by main memory
  - Swapping counts in/out is a disaster
Finding Frequent Pairs

- The hardest problem often turns out to be finding the frequent \textit{pairs} of items \{i_1, i_2\}
  - \textbf{Why?} Freq. pairs are common, freq. triples are rare
    - \textbf{Why?} Probability of being frequent drops exponentially with size; number of sets grows more slowly with size
- Let’s first concentrate on \textit{pairs}, then extend to larger sets
- The approach:
  - We always need to generate all the itemsets
  - But we would only like to count (keep track) of those itemsets that in the end turn out to be frequent
Naïve Algorithm

- Naïve approach to finding frequent pairs
- Read file once, counting in main memory the occurrences of each pair:
  - From each basket of \( n \) items, generate its \( \frac{n(n-1)}{2} \) pairs by two nested loops
- Fails if \((\#\text{items})^2\) exceeds main memory
  - Remember: \#items can be 100K (Wal-Mart) or 10B (Web pages)
    - Suppose \(10^5\) items, counts are 4-byte integers
    - Number of pairs of items: \(10^5(10^5-1)/2 \approx 5*10^9\)
    - Therefore, \(2*10^{10}\) (20 gigabytes) of memory is needed
Counting Pairs in Memory

Goal: Count the number of occurrences of each pair of items (i,j):

- **Approach 1**: Count all pairs using a matrix
  
- **Approach 2**: Keep a table of triples \([i, j, c] = \) “the count of the pair of items \(\{i, j\}\) is \(c\).”
  - If integers and item ids are 4 bytes, we need approximately 12 bytes for pairs with count > 0
  - Plus some additional overhead for the hashtable
Comparing the 2 Approaches

**Triangular Matrix**

- 4 bytes per pair

**Triples**

- 12 per occurring pair
Comparing the two approaches

- **Approach 1: Triangular Matrix**
  - \( n = \) total number items
  - Count pair of items \( \{i, j\} \) only if \( i < j \)
  - Keep pair counts in lexicographic order:
    - \( \{1,2\}, \{1,3\}, \ldots, \{1,n\}, \{2,3\}, \{2,4\}, \ldots, \{2,n\}, \{3,4\}, \ldots \)
  - Pair \( \{i, j\} \) is at position: \( \left[ n(n - 1) - (n - i)(n - i + 1) \right]/2 + (j - i) \)
  - Total number of pairs \( n(n - 1)/2; \) total bytes = \( O(n^2) \)
  - **Triangular Matrix** requires 4 bytes per pair

- **Approach 2** uses **12 bytes** per occurring pair
  (but only for pairs with count \( > 0 \))

- Approach 2 beats Approach 1 if less than \( 1/3 \) of possible pairs actually occur
Comparing the two approaches

- **Approach 1: Triangular Matrix**
  - \( n \) = total number items
  - Count pair of items \( \{i, j\} \) only if \( i < j \)
  - Keep pair counts in lexicographic order:
    - \( \{1,2\}, \{1,3\}, \ldots, \{1,n\}, \{2,3\}, \{2,4\}, \ldots, \{2,n\}, \{3,4\}, \ldots \)
  - Pair \( \{i, j\} \) is at position:
    - \( \frac{n(n-1)}{2} - (n-i)(n-i+1)/2 + (j-i) \)
  - Total number of pairs \( n(n-1)/2 \); total bytes = \( O(n^2) \)
  - Triangular Matrix requires 4 bytes per pair

- **Approach 2** uses 12 bytes per occurring pair (but only for pairs with count > 0)

- **Approach 2 beats Approach 1** if less than \( \frac{1}{3} \) of possible pairs actually occur

**Problem** is if we have too many items so the pairs do not fit into memory.

Can we do better?
A-Priori Algorithm

- Monotonicity of “Frequent”
- Notion of Candidate Pairs
- Extension to Larger Itemsets
A two-pass approach called **A-Priori** limits the need for main memory

**Key idea: monotonicity**
- If a set of items $I$ appears at least $s$ times, so does every subset $J$ of $I$

**Contrapositive for pairs:**
If item $i$ does not appear in $s$ baskets, then no pair including $i$ can appear in $s$ baskets

**So, how does A-Priori find freq. pairs?**
A-Priori Algorithm – (2)

- **Pass 1:** Read baskets and count in main memory the # of occurrences of each *individual item*
  - Requires only memory proportional to #items

- **Items that appear $\geq s$ times are the frequent items**

- **Pass 2:** Read baskets again and keep track of the count of only those pairs where both elements are frequent (from Pass 1)
  - Requires memory proportional to square of frequent items only (for counts)
  - Plus a list of the frequent items (so you know what must be counted)
Main-Memory: Picture of A-Priori

Green box represents the amount of available main memory. Smaller boxes represent how the memory is used.
You can use the triangular matrix method with $n =$ number of frequent items.

- May save space compared with storing triples.

**Trick:** re-number frequent items 1, 2, ..., and keep a table relating new numbers to original item numbers.
For each \( k \), we construct two sets of \( k \)-tuples (sets of size \( k \)):

- \( C_k = \text{candidate } k \)-tuples = those that might be frequent sets (support \( \geq s \)) based on information from the pass for \( k-1 \)
- \( L_k = \text{the set of truly frequent } k \)-tuples
**Note here we generate new candidates by generating \( C_k \) from \( L_{k-1} \) and \( L_1 \). But that one can be more careful with candidate generation. For example, in \( C_3 \) we know \{b,m,j\} cannot be frequent since \{m,j\} is not frequent.**

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**Example**

- **Hypothetical steps of the A-Priori algorithm**
  - \( C_1 = \{ \{b\} \{c\} \{j\} \{m\} \{n\} \{p\} \} \)
  - Count the support of itemsets in \( C_1 \)
  - Prune non-frequent. We get: \( L_1 = \{ b, c, j, m \} \)
  - Generate \( C_2 = \{ \{b,c\} \{b,j\} \{b,m\} \{c,j\} \{c,m\} \{j,m\} \} \)
  - Count the support of itemsets in \( C_2 \)
  - Prune non-frequent. \( L_2 = \{ \{b,m\} \{b,c\} \{c,m\} \{c,j\} \} \)
  - Generate \( C_3 = \{ \{b,c,m\} \{b,c,j\} \{b,m,j\} \{c,m,j\} \} \)
  - Count the support of itemsets in \( C_3 \)
  - Prune non-frequent. \( L_3 = \{ \{b,c,m\} \} \)
A-Priori for All Frequent Itemsets

- One pass for each $k$ (itemset size)
- Needs room in main memory to count each candidate $k$–tuple
- For typical market-basket data and reasonable support (e.g., 1%), $k = 2$ requires the most memory

Many possible extensions:

- Association rules with intervals:
  - For example: Men over 65 have 2 cars
- Association rules when items are in a taxonomy
  - Bread, Butter $\rightarrow$ FruitJam
  - BakedGoods, MilkProduct $\rightarrow$ PreservedGoods
- Lower the support $s$ as itemset gets bigger
PCY (Park-Chen-Yu) Algorithm

- Improvement to A-Priori
- Exploits Empty Memory on First Pass
- Frequent Buckets
PCY (Park-Chen-Yu) Algorithm

- **Observation:**
  In pass 1 of A-Priori, most memory is idle
  - We store only individual item counts
  - Can we use the idle memory to reduce memory required in pass 2?

- **Pass 1 of PCY:** In addition to item counts, maintain a hash table with as many buckets as fit in memory
  - Keep a count for each bucket into which pairs of items are hashed
    - For each bucket just keep the count, not the actual pairs that hash to the bucket!

**Note:**
Bucket ≠ Basket
PCY Algorithm – First Pass

FOR (each basket) :
    FOR (each item in the basket) :
        add 1 to item’s count;
    FOR (each pair of items) :
        hash the pair to a bucket;
        add 1 to the count for that bucket;

- Few things to note:
  - Pairs of items need to be generated from the input file; they are not present in the file
  - We are not just interested in the presence of a pair, but we need to see whether it is present at least $s$ (support) times
Observations about Buckets

- **Observation**: If a bucket contains a frequent pair, then the bucket is surely frequent
- However, even without any frequent pair, a bucket can still be frequent 😞
  - So, we cannot use the hash to eliminate any member (pair) of a “frequent” bucket
- But, for a bucket with total count less than $s$, none of its pairs can be frequent 😊
  - Pairs that hash to this bucket can be eliminated as candidates (even if the pair consists of 2 frequent items)

- **Pass 2**: Only count pairs that hash to frequent buckets
PCY Algorithm – Between Passes

- Replace the buckets by a bit-vector:
  - 1 means the bucket count exceeded the support $s$ (call it a frequent bucket); 0 means it did not

- 4-byte integer counts are replaced by bits, so the bit-vector requires 1/32 of memory

- Also, decide which items are frequent and list them for the second pass
Count all pairs \( \{i, j\} \) that meet the conditions for being a candidate pair:

1. Both \( i \) and \( j \) are frequent items
2. The pair \( \{i, j\} \) hashes to a bucket whose bit in the bit vector is 1 (i.e., a frequent bucket)

Both conditions are necessary for the pair to have a chance of being frequent
Main-Memory: Picture of PCY

Hash table
Item counts
Frequent items
Bitmap
Counts of candidate pairs

Main memory
Hash table for pairs
Counts of candidate pairs

Pass 1
Pass 2
More Extensions to A-Priori

- The MMDS book covers several other extensions beyond the PCY idea: “Multistage” and “Multihash”

- For reading on your own, Sect. 6.4 of MMDS

- Recommended video (starting about 10:10): https://www.youtube.com/watch?v=AGAkNiQnbjY
Frequent Itemsets in \( \leq 2 \) Passes

- Simple Algorithm
- Savasere-Omiecinski-Navathe (SON) Algorithm
- Toivonen’s Algorithm
Frequent Itemsets in $\leq 2$ Passes

- A-Priori, PCY, etc., take $k$ passes to find frequent itemsets of size $k$

- Can we use fewer passes?

- Use 2 or fewer passes for all sizes, but may miss some frequent itemsets
  - Random sampling
    - Do not sneer; “random sample” is often a cure for the problem of having too large a dataset.
  - SON (Savasere, Omiecinski, and Navathe)
  - Toivonen
Random Sampling (1)

- Take a random sample of the market baskets

- Run a-priori or one of its improvements in main memory
  - So we don’t pay for disk I/O each time we increase the size of itemsets
  - Reduce support threshold proportionally to match the sample size
    - **Example:** if your sample is 1/100 of the baskets, use \( s/100 \) as your support threshold instead of \( s \).
Random Sampling (2)

- **To avoid false positives:** Optionally, verify that the candidate pairs are truly frequent in the entire data set by a second pass.

- **But you don’t catch sets frequent in the whole but not in the sample:**
  - Smaller threshold, e.g., \( s/125 \), helps catch more truly frequent itemsets.
  - But requires more space.
SON Algorithm – (1)

- **SON Algorithm:** Repeatedly read small subsets of the baskets into main memory and run an in-memory algorithm to find all frequent itemsets
  - **Note:** we are not sampling, but processing the entire file in memory-sized chunks

- An itemset becomes a **candidate** if it is found to be frequent in **any** one or more subsets of the baskets.
SON Algorithm – (2)

- On a **second pass**, count all the candidate itemsets and determine which are frequent in the entire set

- **Key “monotonicity” idea**: An itemset cannot be frequent in the entire set of baskets unless it is frequent in at least one subset
Toivonen’s Algorithm: Intro

Pass 1:
- Start with a random sample, but lower the threshold slightly for the sample:
  - Example: if the sample is 1% of the baskets, use $s/125$ as the support threshold rather than $s/100$
- Find frequent itemsets in the sample
- Add to the itemsets that are frequent in the sample the negative border of these itemsets:
  - Negative border: An itemset is in the negative border if it is not frequent in the sample, but all its immediate subsets are
    - Immediate subset = “delete exactly one element”
Example: Negative Border

- \{A,B,C,D\} is in the negative border if and only if:
  1. It is not frequent in the sample, but
  2. All of \{A,B,C\}, \{B,C,D\}, \{A,C,D\}, and \{A,B,D\} are.

Diagram:
- Negative Border
- Frequent Itemsets from Sample
- tripletons
- doubletons
- singletons
Toivonen’s Algorithm

- **Pass 1:**
  - Start with the random sample, but lower the threshold slightly for the subset
  - Add to the itemsets that are frequent in the sample the **negative border** of these itemsets

- **Pass 2:**
  - Count all **candidate frequent itemsets from the first pass**, and also count sets in their **negative border**

- **Key:** If no itemset from the negative border turns out to be frequent, then we found **all** the frequent itemsets.
  - What if we find that something in the negative border is frequent?
    - We must start over again with another sample!
    - Try to choose the support threshold so the probability of failure is low, while the number of itemsets checked on the second pass fits in main-memory.
If Something in the Negative Border Is Frequent . . .

We broke through the negative border. How far does the problem go?

... tripletons

doubletons

singletons

Frequent Itemsets from Sample

Negative Border